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Final Report on ASU Research Funded through Lawrence Livermore National Laboratory Grant ASU XAJ9991/CO

R. Calhoun, J. Sommer

January 22, 2004

Disclaimer

This work was performed under the auspices of the U.S. Department of Energy by University of California, Lawrence Livermore National Laboratory under Contract W-7405-Eng-48.

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Advanced Sensor Integration into NARAC's Atmospheric Data Assimilation Program

Principal Investigator: Dr. R. Calhoun
Student Researcher: Mr. J. Sommer

Assistant Professor of Mechanical & Aerospace Engineering
Arizona State University

December 2003

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1. Goal of Research

The line of inquiry which the ASU lidar group has been investigating, with collaboration and support from LLNL, is to create approaches and algorithms for better utilizing the rich information available through modern remote sensors in dispersion modeling systems. In particular, our goal is to *create a lidar-data-driven dispersion model mode in ADAPT/LODI*. This report describes progress towards this goal during the 2002/2003 academic year. Because of the nature of lidar data and the necessity to utilize additional information, both numerical and measured, this is essentially a data retrieval and data fusion project. With the current generation of commercially available lidar, the scope of the domain in which we are interested is initially 4 to 14 kilometers in radius, where the potentially scanned domain is roughly hemispherical. Figure 1, for example, taken from a recent lidar deployment in Oklahoma City, shows visually the most typical range of the domain that can be probed with the ASU lidar. Ranges 2 or 3 times the distance to the cluster of buildings in the photograph can be probed with a properly functioning, commercially available lidar. This could be of significant value for protecting key buildings with roof-top located remote sensors coupled with dispersion models.

There are many potentially useful approaches toward the goal. These range from simple, faster approaches to complex, numerically and time intensive methods. In order to be aligned with the nature and intent of prominent dispersion modeling systems such as that operated in real-time by NARAC at Lawrence Livermore National Laboratory, we have chosen to initially develop faster, less numerically intensive approaches. *Our strategy is to use simple, fast algorithms combined with supplementary data when required and to achieve accuracy not through high model complexity but rather through high frequency updates, i.e. through tight coupling with remote sensing data streams.*

In summary, our goal was to investigate and build prototypes for algorithms allowing the spatial and temporal richness of modern remote sensing data to be utilized in dispersion modeling systems. We envision remote sensors mounted potentially on building tops, scanning regions of potential threat, with a coupling to a dispersion model allowing both diagnosis and predictive description of evolving scenarios.

Figure 1. Oklahoma City downtown urban center as seen from the ASU Lidar location during JU2003, July, 2003.

2. Value and Challenges of Lidar Data

In order to properly use lidar data, we must be careful to understand its unique benefits and challenges. Indeed, one of the products of the funded research is an improved understanding of how to use and process data from commercially available lidar. This is a necessary precondition for the development of coupled sensor/model dispersion systems. In this section, we describe both the unique strengths and caveats of using lidar data which we understand more clearly as a result of our research effort.

First, a coherent Doppler lidar can operate in an urban environment, rapidly scanning large areas and volumes of the atmosphere. Because the products are both radial velocity fields and backscatter coefficients, clouds of above ambient aerosol can be directly tracked across a downtown region – while simultaneously acquiring information on the accompanying wind fields. For example, Figure 2 shows the ASU lidar tracking aerosol plumes across the Oklahoma City downtown area during the JU2003 experiment. The ASU and ARL lidar teams collaborated to probe the transport and dispersion of smoke plumes from firework displays on the 4^{th} of July, 2003. Note that initial releases of the smoke were elevated and spherical in shape. The ASU team performed two level Planned Position Indicator (PPI) scans, scans with constant elevation and varying azimuth angles, which allowed our team to track in real-time plume shape evolution and trajectory. In fact, real-time trajectory information was communicated to the ARL team by cell phone in order to check whether their scanning methods would be expected to capture the approaching plumes. The ARL team probed the plumes as they passed through vertical-horizontal, cross-sectional planes downstream with two Range Height Indicator (RHI) scans. RHI scans have varying elevation and constant azimuth angles. Given the dual sensor arrangement and the unique capabilities of the coherent Doppler lidar, it may be possible to reconstruct both three-dimensional deformations and trajectories of these firework smoke plumes.

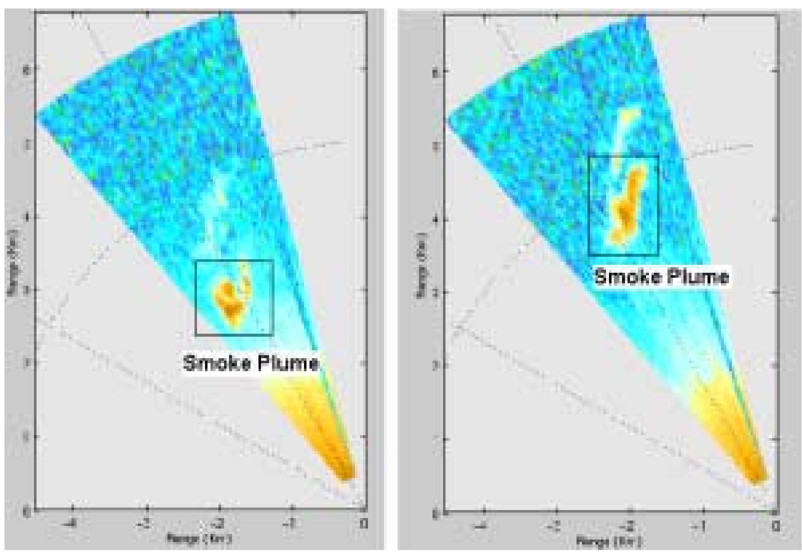

Figure 2. ASU lidar tracks smoke plumes in Oklahoma City (July 4, 2003). PPI scans show horizontal shape and movement of smoke plumes. Winds were toward the north with small westerly component (approximately 7 m/s).

Unique challenges are associated with the shape of the volume probed by the lidar. Returns are produced from cylindrical volumes of air roughly 10 cm in diameter by 60 m in length. In the following, we describe in more detail how both the noise level inherent in lidar and the probing volume affect the possibility of obtaining turbulence information.

During several experiments, coherent Doppler lidar have performed "stares", where the position of the beam is held fixed, in order to allow the possibility of calculating turbulence statistics along the beam. For example, in JU2003, the ARL lidar team performed a "stare" scan towards the "crane-tower" which was instrumented with an array of sonic anemometers, and the ASU lidar team performed a "stare" over the PNNL radar profiler site and through the CBD (see Figure 3). The lidar scans close to the sonic measurements will allow us to compare variances and spectral estimates of turbulence from both instruments. Although lidar data has high enough temporal resolution for resolving turbulent scales (up to 5Hz or even 10Hz – averaging over 100 or 50 laser pulses, respectively), its unique spatial averaging over a relatively big cylindrical volume represents severe difficulty in direct turbulence calculations from the raw lidar data. As an illustration, spectra of sonic and lidar data are given in Figures 4 & 5. While in "sonic spectra", inertial sub range that undergoes the Kolmogorov $k^{-5/3}$ law is evident (Figure 4), this subrange cannot be found in the "lidar spectra" (Figure 5). This is not surprising considering the fact that lidar velocity comes from a scale much larger than most turbulence length scales. In addition, a careful analysis of the size of the radial velocity errors and how these errors propagate to turbulence statistics must be performed. For these reasons, one must proceed with caution calculating turbulence statistics with lidar data. More complex methods must be used if one wishes to obtain a more complete representation of the turbulent field (see, for example, Frehlich et al. 1998). Turbulence information can also be recovered from lidar data through four-dimensional variational data assimilation (4DVAR) in which eddy and thermal diffusivity are treated as part of the control variables in data assimilation.

Figure 3. ASU Lidar staring over Oklahoma City during JU2003.

Another challenge in lidar data processing is handling the noise. Lenschow et al. (2000) discuss expressions for correcting second- through fourth-order moments of data contaminated by random uncorrelated noise. Data analysis methods must be robust enough to resist large random observational errors/noise. The reduction of the speckle patterns, which represent the random distribution of atmospheric irregularities, involves rigorous computer processing. Initial de-noising of data is already implemented in the ASU's Matlab scripts, however, more rigorous and sophisticated filter algorithms closely specialized for lidar output are needed. Strict statistical formalism must be respected for the evaluation of statistical significance of data. This is very critical in calculation of higher moments where uncertainty is multiplicative (with a factor greater than one, depending of the moment order) of the original uncertainty.

Preliminary post-processing of the ASU lidar data provides an example of these challenges. Figure 6 shows radial velocity and rms of radial velocity obtained from the "stare" scan towards the CBD averaged over 5 minutes. A significant drop in velocity can be seen just in front of the CBD, and at the same position, a substantial increase in rms velocity can be seen. Time series of radial velocity in gate 30 and 58 are presented in Figure 7. Gate 30, at approximately 2.4 km from the lidar is several hundred meters before the CBD while gate 58 at 4.2 km corresponds to a position just beyond the CBD. In the given example, noise is significantly increased in the downstream vicinity of the CBD. At the distances further from CBD, noise is increasing due to the signal weakening. Some noise effects can be solved in by use of simple median filter. Velocity obtained in this way is presented in Figure 8 for the same scan as Figure 6.

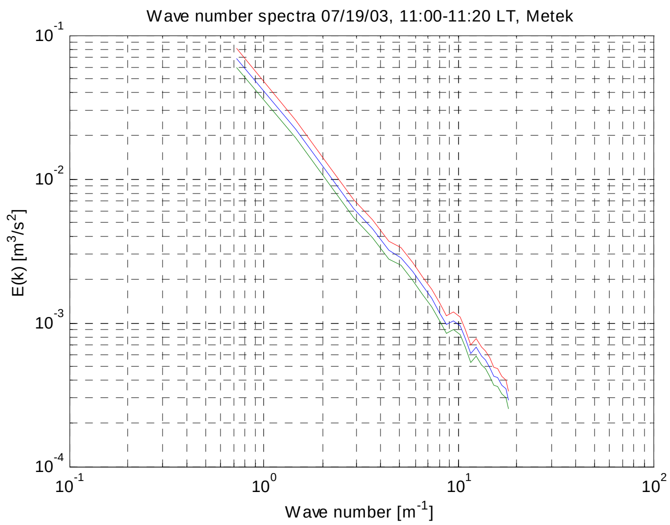

Figure 4. Energy spectrum calculated from sonic anemometer data evidently follows the –5/3 slope. Lines present 95% confidence interval.

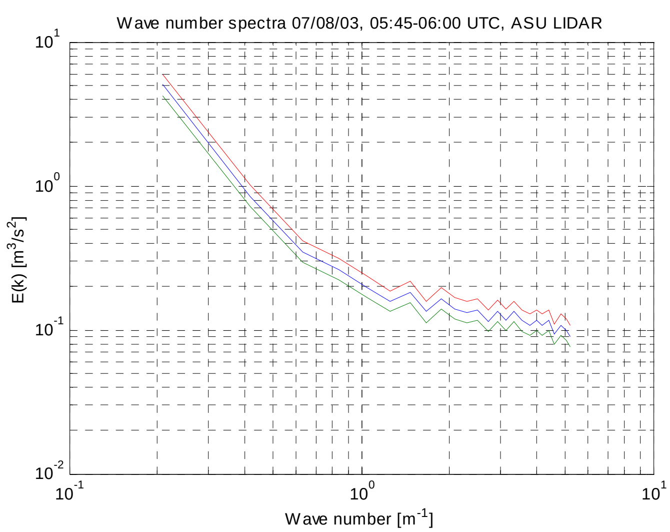

Figure 5. Energy spectra calculated from lidar data do not follow the –5/3 slope. Lines present 95% confidence interval.

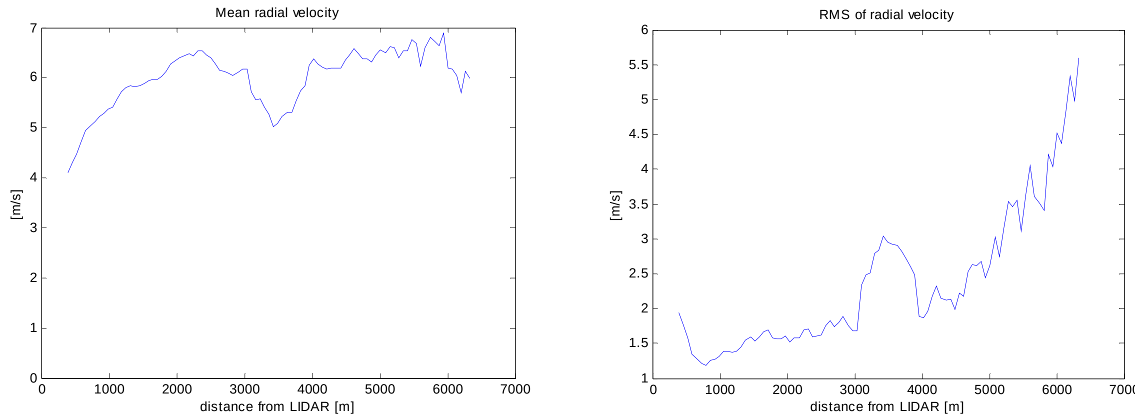

Figure 6. Radial velocity and variance from stare scan (averaging over 5 minutes).

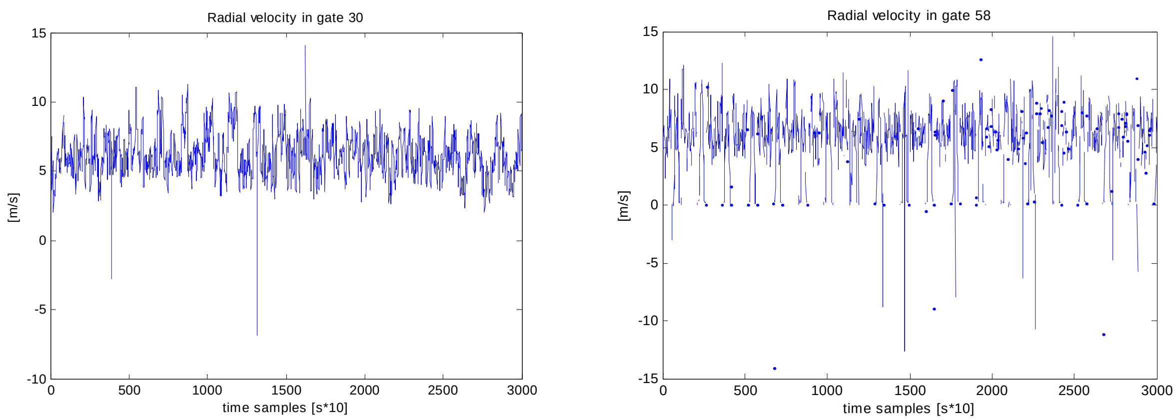

Figure 7. 5 minutes time trace of radial velocity in gate 30 and 58.

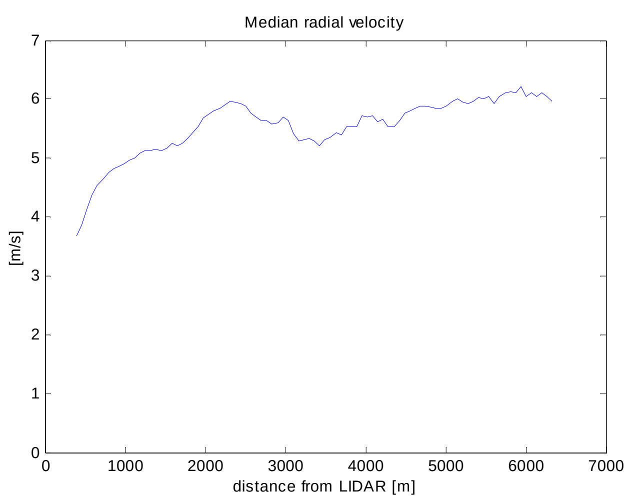

Figure 8. Median radial velocity. Compare with mean velocity in Figure 6.

3. Review of Approaches

We reviewed a variety of candidate algorithms for this research program. Our initial impression, after a first review of the literature, was that *optimal estimation* (Cole and Wilson 1994) was a promising candidate. However, more careful analysis showed that for our purposes of retrieval of winds quickly from potentially one radial velocity field, additional approaches were required. Using optimal estimation strategies could prove useful in more advanced data fusion techniques which could be used potentially later in the evolution of the algorithms developed here. We also investigated four-dimensional variational data assimilation (4DVAR) techniques (Lin, et. al 2001). Because of slow speed of execution and complexity, 4DVAR did not seem appropriate for the purposes and scope of this project. Additionally, we reviewed several techniques from radar processing. In particular, personal communication with A. Shapiro (Shapiro et al. 1995***;*** University of Oklahoma) has helped to clarify how well single Doppler velocity retrieval methods from the radar field may work with lidar data. These methods remain very promising avenues of investigation, but also required a level of effort larger than our 1 graduate student scope of work. We therefore decided to focus our attention on the simplest wind retrieval algorithms that we discovered – sector VAD and feature tracking. These algorithms will be described more carefully below along with our experience using and implementing them as test prototypes in our lidar-postprocessing environment.

4. Obtaining Wind Fields

This section deals with retrieval of wind fields from radial velocity vectors, specifically our applied research exploring our implementations of sector VAD and feature tracking algorithms.

4.1 Sector VAD Approach

Sector VAD algorithms are simply an adaptation of the well known VAD algorithm (Rob

Newsom, personal communication) requiring the assumption of homogeneity of winds over a large domain and probing that domain from a variety of directions. Geometrical arguments allow the recovery of two dimensional wind vectors from radial velocity fields. One may apply the VAD algorithm on a smaller sector, assuming homogeneity only over the smaller sector. A central challenge of this approach is an instability inherent in the mathematics and noisy data as the sector size decreases. Accuracy is therefore low and resolution is sacrificed; however, a rough idea of wind vectors can be obtained in a low resolution manner very rapidly.

The mathematics of the VAD algorithm are well known and are available in many places. The description provided below is adapted from personal communication with R. Newsom of CIRES.

Traditional VAD processing.

- First filter out suspect data.
- Process each range gate separately.
- Using data from a full (360^o) PPI scan, apply the following procedure to each range gate:

1)Define the following cost function

$$L = \sum_n \left(\mathbf{u} \cdot \hat{\mathbf{r}}_n - u_{r_n}\right)^2 \qquad \textbf{Eqn. 1}$$

where

$\hat{r}_n = \sin(az)\cos(el)\hat{\mathbf{x}} + \cos(az)\cos(el)\hat{\mathbf{y}} + \sin(el)\hat{\mathbf{z}}$, Radial unit vector from the lidar to a point on the "range ring."

$u_{r_n} =$ Radial velocity measured by the lidar

$\mathbf{u} = u\hat{\mathbf{x}} + v\hat{\mathbf{y}}$, this is the vector we're solving for.

$\sum_n$ = summation over all the radial velocity measurements within the range ring

2) Minimize L with respect to u and v. Compute

$$\frac{\partial L}{\partial u} = 2\sum_n \left(\mathbf{u} \cdot \hat{\mathbf{r}}_n - u_{r_n}\right)\sin(az_n)\cos(el_n) \qquad \textbf{Eqn. 2}$$

$$\frac{\partial L}{\partial v} = 2\sum_n \left(\mathbf{u}\cdot\hat{\mathbf{r}}_n - u_{r_n}\right)\cos(az_n)\cos(el_n) \qquad \textbf{Eqn. 3}$$

Setting $\frac{\partial L}{\partial u} = 0$ and $\frac{\partial L}{\partial v} = 0$ gives a 2x2 linear system. Solve it for u and v.

3) Build the vertical profile of u and v by repeating steps (1) and (2) for each range ring. The height of each range ring is z = rsin(el).

We implemented this algorithm in our Matlab, lidar processing scripts which were developed as part of this grant. An example of the results can be seen in Figure 9. We tested the effect of various sector sizes, discovering as expected instability with sectors that are too small. Figure 9 shows approximately the highest resolution that we could reasonably obtain using this approach. (The number of radial velocities available from the original data is approximately 50 along the length where the vectors appear below.) Primary advantages of this algorithm are speed, simplicity and the lack of any special requirements concerning advection of features relative to scan speed.

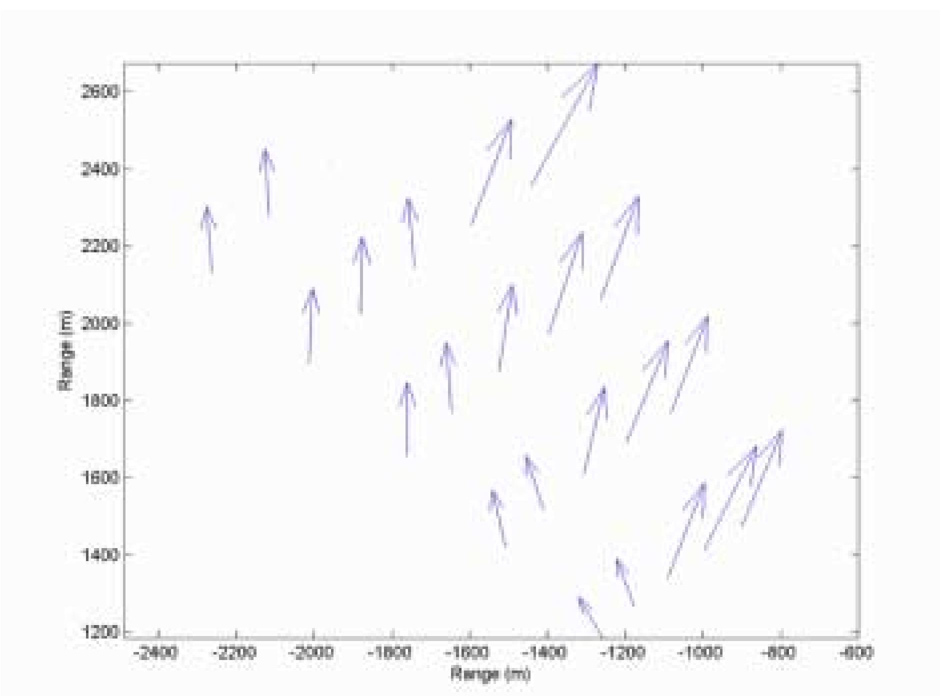

Figure 9. Vectors retrieved from single Doppler Lidar radial velocity field - JU2003 data (low elevation PPI

looking toward the CBD

4.2 Feature Tracking

In collaboration with LLNL, the ASU lidar team has developed prototype retrieval methods for estimating wind vectors from radial velocity fields based on feature tracking approaches (see Tuttle & Foote 1990, Mayor & Eloranta 2001). Figure 10 shows the basic idea of feature tracking, adapted from Tuttle & Foote (1990). Equation 4

$$R = \frac{\sum Z_1(i)Z_2(i) - n^{-1}\sum Z_1(i)Z_2(i)}{\left(\left(\sum Z_1{}^2(i) - n\overline{Z}_1{}^2\right)\left(\sum Z_2{}^2(i) - n\overline{Z}_2{}^2\right)\right)^5} \qquad \textbf{Eqn. 4}.$$

shows the cross correlation (R) which is calculated and then maximized to obtain the direction and distance that a feature has moved during a time step (Z is, in our case, a column vector of radial velocities).

We found that tracking using radial velocities appeared to be more effective than tracking inhomogeneities in the backscatter field. Figure 11 shows the magnitude of the cross correlation plotted by color. We implemented both our own cross correlation calculation and found correlation functions in the Matlab image processing toolbox. Note that, in the decade or so since Tuttle's original paper and due at least in part to special effects research for the movie industry, cross-correlation algorithms, which consume most of the time during with these methods, have improved in terms of execution speed by up to an order of magnitude.

Advantages of this method are accuracy of the vector field and more numerical stability than the VAD method. In addition, the resolution decrease is not as pronounced as in the VAD method. However, some restrictions are naturally inherent in the method. Figure 12 shows the original domain, the search template, and the resulting smaller domain size, and indicates how the domain size is decreased on the edges in relation to the search template size. Interestingly, approximate knowledge of wind direction such as can be available with the sector VAD may allow methods which decrease this buffer zone around the edges. This would be based on the fact that it is unnecessary to search for a feature in directions that are approximately upwind, since features do not advect upwind. Figure 13 shows vector retrieval on a PPI plane of ASU lidar data (JU2003).

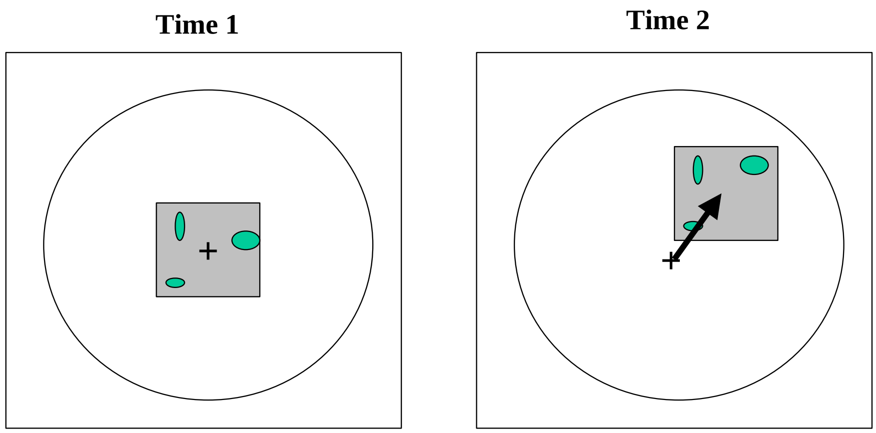

Figure 10. Basic idea of feature tracking algorithm – adapted from Tuttle 1990. A region or “template” is selected and subsequent realizations of the flow field are searched with a moving template. The location of the maximum of a cross-correlation function provides an estimate of how features have moved, and therefore, a vector.

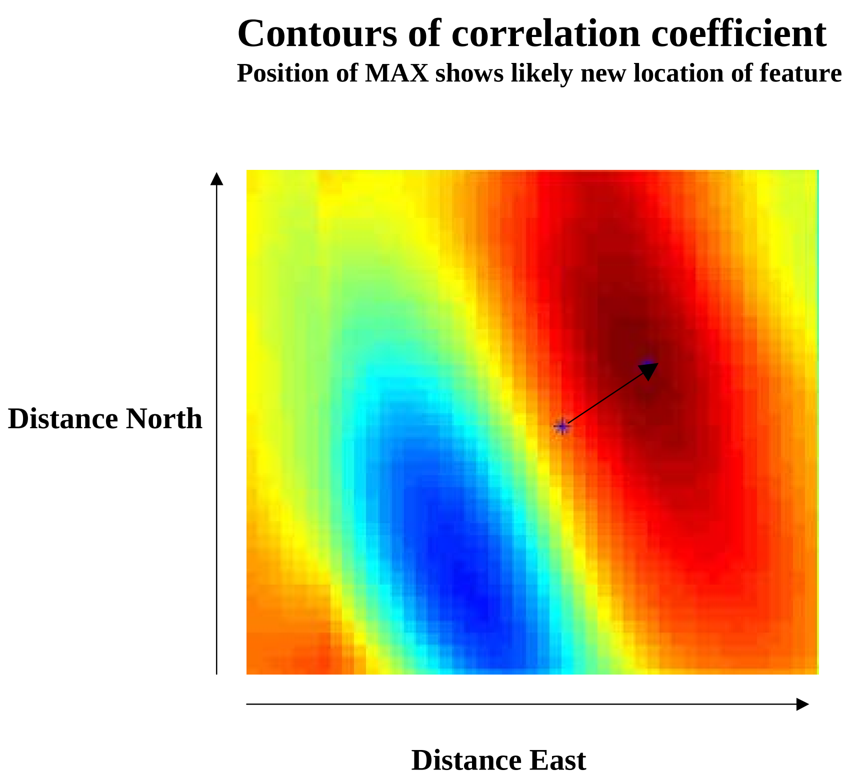

Figure 11. Cross correlation plotted by color for ASU feature tracking algorithm.

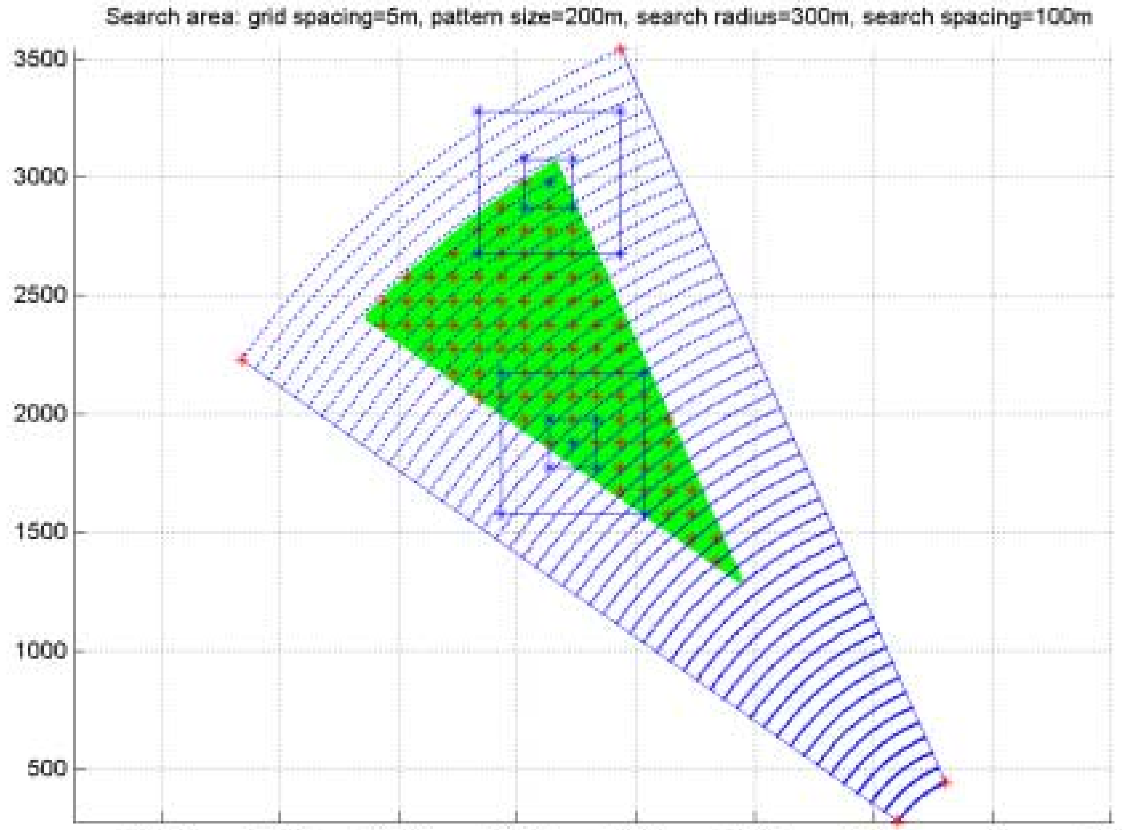

Figure 12. Plot show search domain templates and resulting restrictions on size of retrieved domain (green) compared to original domain (blue).

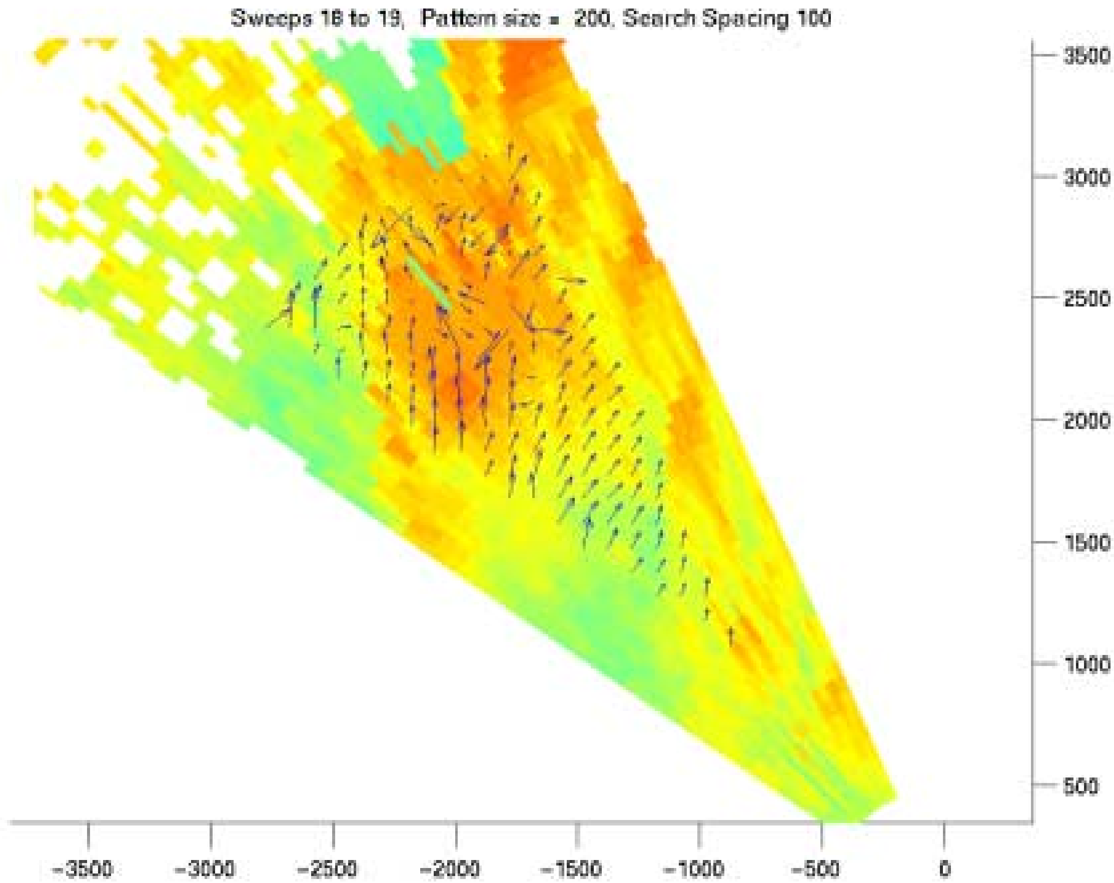

Figure 13. Velocity vectors retrieved from single Doppler (ASU lidar) data on a plane during JU2003. Vectors are calculated by tracking correlated patterns of radial velocity.

5. Review of Accomplishments

We summarize below the accomplishments of this research project:

1. Training of students to operate and analyze data from coherent Doppler lidar.
2. Development of open source lidar postprocessing scripts
3. Deepened understanding of nature of lidar data
3. Review of literature relevant to coupling lidar and dispersion models
4. Investigation of methods of wind vector retrieval using ASU prototypes
    a. Built prototype for VAD sector retrieval and testing
    b. Built cross-correlation retrieval method and testing
5. Presentations to LLNL, AGU, and ASU communities on methods developed
6. Funded Mr. Sommer through 9 months of Masters degree effort at ASU.

One the overall accomplishments of this small research effort described here was to effectively "prime the pump" or place the ASU lidar team in a position to absorb and expand radar processing numerical techniques for lidar processing. The primary graduate student will continue the line of inquiry described here for another semester in order to complete a Master's thesis.

6. Continuing Work

As can be seen in the previous section, the ASU lidar group has been productively stimulated by the supporting LLNL collaboration and good progress towards the ultimate goal of coupling lidar remote sensing with dispersion modeling systems has been completed.
Ongoing research by Mr. Sommer is addressing the following continuations of the completed research:

1. Implementing vector cleaning strategies and extrapolating vectors toward edges of the domain.
2. Merging VAD and cross correlation methods to produce vector field both at low and higher elevations.
3. Testing ADAPT/LODI runs with lidar data from JU2003.
4. Investigating the possibility of merging cross correlation and traditional lidar postprocessing to improve wind vector field accuracy, i.e. allow lidar signal processing to determine radial component of wind vector and use cross correlation method to determine other components. This provides some redundancy and error checking opportunities since the cross correlation method independently provides also the radial component.

7. Personnel Supported

The primary researcher for this project has been Master's Candidate Jeffrey Sommer of ASU's Mechanical and Aerospace Engineering Department. The research was guided by Assist. Prof. R. Calhoun also of the ASU Mechanical and Aerospace Department. Early work on the initial postprocessing scripts was completed by J. Porter and R. Heap both of whom worked under the guidance of Dr. Calhoun at ASU.

8. Software Package

A major product of this research project has been open source lidar data processing tools. Current commercially engineered lidar, such as that produced by Coherent Technologies, Inc (CTI), come equipped with a capable GUI based display and postprocessing software. However, the software is proprietary, and researchers require the full flexibility of access to the data with open source software scripts. Due to LLNL support and key collaborations with CTI and NOAA's Environmental Technology Laboratory, the ASU lidar team has produced a set of Matlab scripts that meet these needs. These scripts allow the researcher to full flexibility to manipulate lidar data in a standardized and popular scripting environment (Matlab). ASU has provided the JU2003 management, the Army Research Laboratory, the Army Research Office, and NOAA's ETL with the ASU postprocessing scripts. Recently Dr. Kottmeier of the University of Karlsruhe, Germany, has requested a collaboration with ASU to obtain the lidar postprocessing scripts. (Dr. Kottmeier visited Dr. Calhoun in 2002 to discuss commercially available lidar. He recently ordered a lidar system (CTI WindTracer) similar to the ASU lidar which will be delivered in 2004 to the University of Karlsruhe). This contribution to the research community was made possible in part through funds provided by LLNL through this research project. The feature tracking and sector VAD algorithms are also available to LLNL researchers.

9. Presentations

Dr. Calhoun and Dr. Fernando of ASU presented a poster at the American Geophysical Union in San Francisco, December 2003 entitled "A Survey of Lidar Data for the Joint Urban 2003 Experiment". The postprocessing of the lidar data was made possible because of the LLNL/ASU research effort described here. Mr. Sommer is expected to continue this research to complete his Master's thesis in 2004. Dr. Calhoun also presented a final project seminar to interested members of LLNL's Atmospheric Science Division Nov. 7, 2003.

10. Acknowledgements

We are deeply grateful to the following collaborators without whom this work would not have been possible: Julie Lundquist (LLNL), G. Sugiyama (LLNL), W. Bach (ARO), M. Princevac (ASU), R. Heap (ASU), J. Sommer (ASU), R. Newsom (CIRES), J. Tuttle (NCAR), A. Shapiro (Univ. of Oklahoma), H.J.S. Fernando (ASU), and R. Banta (NOAA).

This project was supported by LLNL Subcontract B523235 with the Arizona Board of

Regents for and on behalf of Arizona State University. LLNL work is performed under the auspices of the U. S. Department of Energy by the University of California, Lawrence Livermore National Laboratory under contract No. W-7405-ENG-48.

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